Examining the Interaction of Growing Crops with Local Climate Using a Coupled Crop–Climate Model

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(Manuscript received 21 February 2008, in final form 4 September 2008)

ABSTRACT

This paper examines to what extent crops and their environment should be viewed as a coupled system. Crop impact assessments currently use climate model output offline to drive process-based crop models. However, in regions where local climate is sensitive to land surface conditions more consistent assessments may be produced with the crop model embedded within the land surface scheme of the climate model. Using a recently developed coupled crop–climate model, the sensitivity of local climate, in particular climate variability, to climatically forced variations in crop growth throughout the tropics is examined by comparing climates simulated with dynamic and prescribed seasonal growth of croplands.

Interannual variations in land surface properties associated with variations in crop growth and development were found to have significant impacts on near-surface fluxes and climate; for example, growing season temperature variability was increased by up to 40% by the inclusion of dynamic crops. The impact was greatest in dry years where the response of crop growth to soil moisture deficits enhanced the associated warming via a reduction in evaporation. Parts of the Sahel, India, Brazil, and southern Africa were identified where local climate variability is sensitive to variations in crop growth, and where crop yield is sensitive to variations in surface temperature. Therefore, offline seasonal forecasting methodologies in these regions may underestimate crop yield variability. The inclusion of dynamic crops also altered the mean climate of the humid tropics, highlighting the importance of including dynamical vegetation within climate models.

1. Introduction

Crop growth, development, and yield are affected by numerous environmental variables, notably rainfall (via soil water fluctuations), temperature, humidity, and the chemical composition of the atmosphere itself (e.g., CO_2 concentration). These factors, in combination with the control of day length on the development of some crop species, have led to the distribution of crops across the globe seen today. Currently crops occupy approximately 12% of the land surface (Ramankutty and Foley 1998). While technology explains a large degree of the spatial variability in crop productivity, particularly between developed and developing countries, variations in climate have a substantial impact on the level of productivity on a year-to-year basis. Several studies have examined the relationship between crop productivity and climate. Most recently, Lobell and Field (2007) found that at the global scale significant correlations exist between year-to-year variations in growing season rainfall and temperature and the yield of several major food crops. Stige et al. (2006) examined the link between indices of climate variability such as ENSO and NAO and crop yields in Africa, while Krishna Kumar et al. (2004) and Challinor et al. (2003) have found strong relationships between monsoon rainfall

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DOI: 10.1175/2008JCLI2494.1

variations and the yield of crops grown in India at the country and regional level, respectively.

In meteorology, many studies have examined the response of climate to changes in either vegetation cover or land surface characteristics. In a landmark study, Charney (1975) used a conceptual model to examine the role of surface albedo in sustaining the circulation over, and hence the location of, the desert margins of northern Africa. Today, general circulation models (GCMs) are used to investigate the influence of vegetation coverage and climate. The representation of vegetation within GCMs has increased in complexity in recent years, enabling the examination of more specific questions, such as the impact on climate of deforestation in the tropical rain forests (Zhang et al. 1996).

Land–atmosphere interactions are important in determining climate at the seasonal time scale (Lawrence and Slingo 2004b). The Global Land–Atmosphere Coupling Experiment (GLACE) study (Koster et al. 2006) has compared several atmospheric GCMs based on their land–atmosphere coupling strength, the ability of a soil moisture anomaly to determine intraseasonal variations in surface climate and precipitation. At longer time scales there is some modeling evidence that either soil moisture or vegetation variations can influence climate. Zeng et al. (1999) showed that both soil moisture and dynamic vegetation variations enhanced the interdecadal variability of Sahelian rainfall within their model.

The importance of croplands for the determination of local climate has only recently been recognized in the global climate modeling community. McPherson et al. (2004) examined meteorological observations over the corn belt of the central United States and found that the difference in vegetation dynamics between the managed cropland and the natural grasslands gave rise to local anomalies in near-surface temperature and humidity. Tsvetsinskaya et al. (2001a) incorporated dynamical representations of crop growth in a regional climate model and found it improved the simulation of near-surface climate over a homogeneous cropped region in the central United States (Tsvetsinskaya et al. 2001b). As these models are developed in the future, the management aspects of cropping systems should be given consideration; for example, the use of irrigation to alleviate soil moisture deficits has been shown to have significant cooling effects on local climate, resulting from an increase in evaporation (Bonfils and Lobell 2007).

The hypothesis of this study is that climate-induced variability in crop growth results in variability of land surface properties (albedo, roughness, vegetation cover), which in turn alters the surface turbulent and radiative fluxes, thereby providing a conduit for an influence of crop growth on the atmosphere. To evaluate this hypothesis we utilize a crop–climate model that simulates the two-way interactions between crop growth and climate. In section 2 we describe the crop–climate model, section 3 evaluates the simulated influence of climate variations on crops, and section 4 examines the influence of the crop variations on climate variability. Results are discussed in section 5 and conclusions drawn in section 6.

2. Crop–climate model

The simulations in this study have been performed with a new coupled crop–climate model described in Osborne et al. (2007). This model was developed by incorporating growth and development routines of a large area crop model [the General Large Area Model for Annual Crops (GLAM)] into the land surface scheme [Met Office Surface Exchange Scheme (MOSES)] of the third Met Office Hadley Centre Atmospheric Model (HadAM3).

GLAM (Challinor et al. 2004) is an offline crop model developed to simulate crop growth and yield for tropical rain-fed crops at spatial scales synonymous with that of climate model output. GLAM was first parameterized to simulate groundnut production in India following the discovery of a strong relationship between weather, in particular rainfall, and crop yield at large spatial scales (Challinor et al. 2003). The version of GLAM calibrated to simulate groundnut was used as the basis for the crop parameterization in GLAM–MOSES. For this study it is considered to represent the behavior of a typical rain-fed annual crop grown in the tropics where the timing of the growing season and the variation in growth from year to year are both determined by variations in rainfall. Significant relationships between yield and climate have been found for other crops as well as groundnut in India (Krishna Kumar et al. 2004) and Africa (Stige et al. 2006). We hypothesize, therefore, that groundnut has similar growth patterns in response to the environment as other annual crops in the tropics, and that the behavior in the model is illustrative of other annual crops. Parameterization of other crops within GLAM–MOSES is ongoing and will enable the broader examination of crop–climate interactions for a range of cropping systems worldwide.

While operating at relatively large spatial scales compared to many other crop growth models developed for field-scale applications (e.g., the CROPGRO model; Boote et al. 1998), GLAM adopts a process-based approach and simulates the growth of state variables for crop leaf area, root depth, and density, and aboveground biomass from which yield is derived via

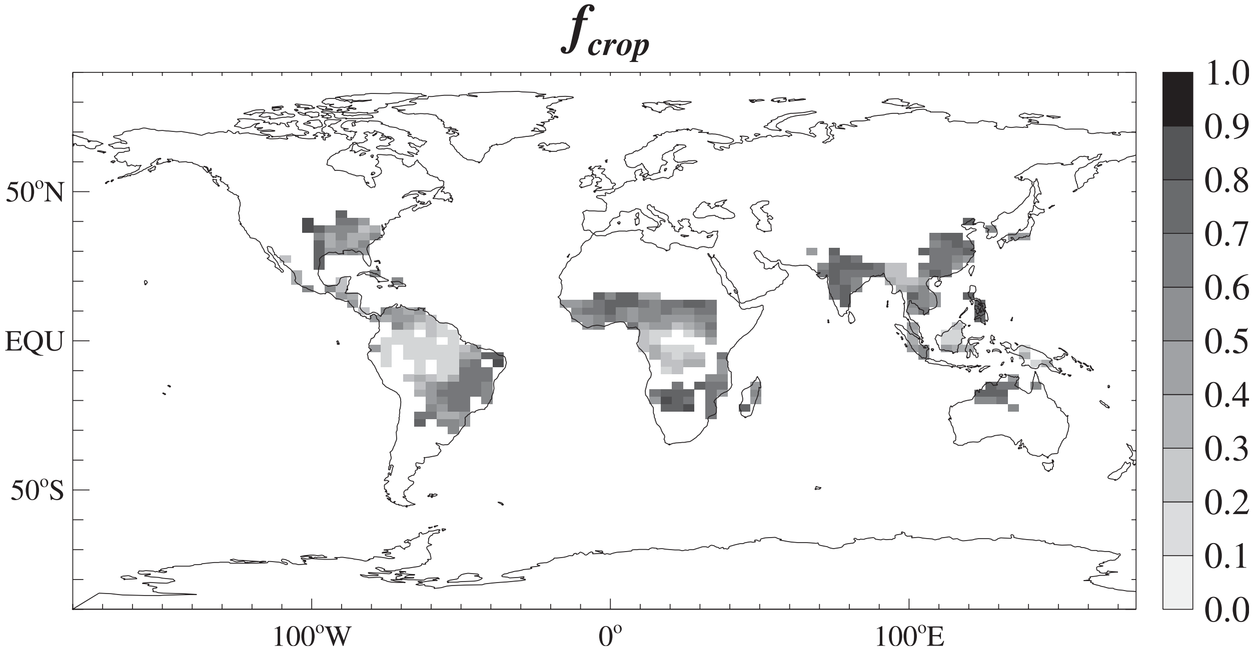

FIG. 1. Fractional coverage of crop tile in both GROW and FIX simulations.

a time-varying harvest index. The crop-sowing date is dependent on time of year (prescribed crop-sowing windows varying latitudinally, see below) and soil moisture content (i.e., when soil moisture content is greater than 50% of field capacity) representing the requirement of sufficient soil moisture for crop establishment in the semiarid tropics (Sivakumar 1992). Sufficient datasets on crop sowing do not exist to examine the skill of the sowing date algorithm in simulating interannual variability in the crop-sowing date. However, it is included because it represents real-world behavior better than the prescription of a fixed sowing date. A similar parameterization is used in the Système d'Analyse Régionale des Risques Agroclimatologique-Habillé (SARRAH) crop model when applied to West Africa based on agricultural surveys (Sultan et al. 2005), and the sowing date of tropical crops in the Lund–Potsdam–Jena managed land (LPJ-mL) agroecosystem model is determined by precipitation (Bondeau et al. 2007).

Once sown, the crop proceeds through various phenological stages at a developmental rate dependent on thermal time (the product of time and temperature above a crop-specific base temperature). A thermal time requirement for crop emergence was added to the first version of GLAM–MOSES based on the observations of Angus et al. (1981). Therefore, crop growth responds to variations in weather and soil moisture conditions at intra- and interseasonal time scales. Following harvest, another crop can sown be if the soil moisture criterion is satisfied. This allows for the representation of multiple crops per year in the humid tropics and rabi (winter) crops in India (USDA 1994), although we recognize that many of these crops require irrigation to reach maturity, a process currently not included in the model.

MOSES (Cox et al. 1999) determines the surface fluxes of moisture and heat that are passed to the lowest level in the atmospheric model, and the drag on the near-surface winds is determined by surface characteristics. The most recent version includes a tiling scheme to represent heterogeneity of surface cover within a climate model grid box (Essery et al. 2003). Currently nine surface tiles exist—five vegetation tiles, or plant functional types (PFTs; broadleaf and needleleaf tree, and C3 and C4 grasses and shrubs), and four nonvegetation tiles (urban, lake, bare soil, and ice). Aboveground, each vegetation tile is characterized by a leaf area index (LAI), canopy height, and canopy water and heat capacities. Belowground, each PFT is prescribed a fixed rooting depth, which is used to determine the fractional distribution of roots in each of the four soil levels. Variations in the size of these components will affect the determination of fluxes from the tile. The surface albedo of each tile is determined from the combination of vegetation albedo, leaf area index, and the underlying soil albedo (modified by surface soil moisture content). In the version used here, MOSES has constant vegetation characteristics throughout the

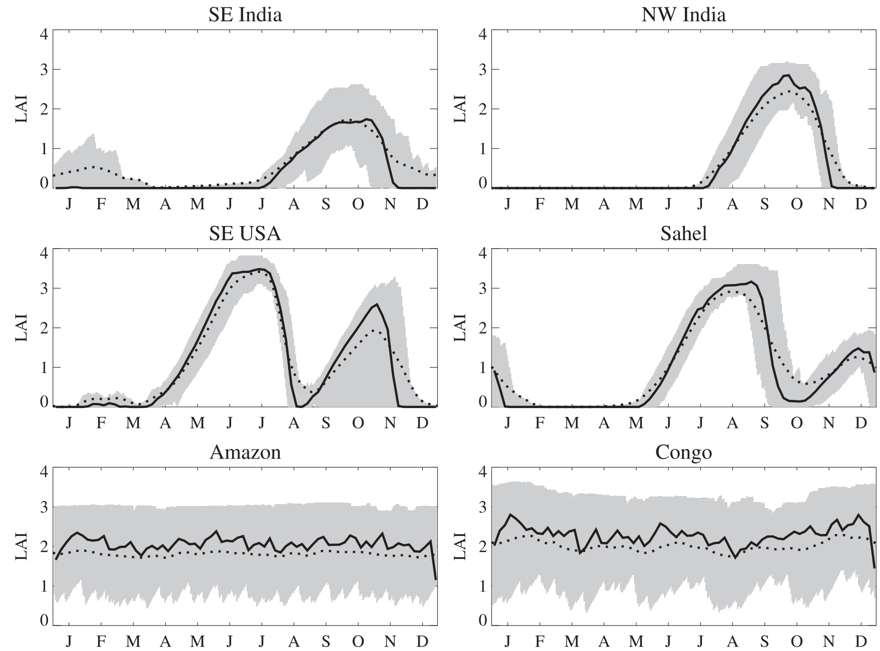

FIG. 2. Example time series of crop leaf area index from GROW simulation. The gray shading is the interquartile range, the dotted line is the mean, and the solid line is the median (5-day mean) used to prescribe crop characteristics in FIX simulation.

annual cycle. The only components that interact with the environment are the soil moisture conditions and stomatal conductance, which controls the rate of water loss from the crop via transpiration.

Osborne et al. (2007) developed a dynamic crop tile by incorporating crop growth functions within the MOSES framework to alter vegetation properties (leaf area index, canopy height, root depth) of a crop PFT. Because the number of tiles in MOSES is fixed, the shrub tile was usurped for use as the crop tile. Each tile shares the same soil moisture store so the simulated crop was fully consistent both with the simulated climate and soil moisture environment of the other PFTs. GLAM–MOSES requires the specification of growing area and a spatially varying sowing window. Osborne et al. (2007) adapted a global agroecological zones methodology (Fischer et al. 2002) to determine where and when it was feasible to simulate crop growth and productivity given the climate of HadAM3. Soil moisture and temperature diagnostics from a present-day climate simulation of HadAM3 were used to define potential crop-growing periods at each grid point based on crop-specific criteria. Points with potential growing periods were selected as suitable for the simulation of crops by GLAM–MOSES, and the range of start dates of potential growing periods was used to define months within which GLAM–MOSES was allowed to determine the actual sowing date. The distribution of the start dates was closely related to the seasonal evolution of temperature, so the size of sowing windows was prescribed as a decreasing function of latitude.

In reality, crops within and outside of this region may be cultivated and supported with irrigation. Therefore, the absence of irrigation in this study limits the results' applicability to regions where irrigation is prevalent. Bonfils and Lobell (2007) showed that irrigation has had a cooling impact on near-surface climate in irrigated regions because of enhanced surface evaporation and a reduction in sensible heating. How irrigation impacts climate variability is less clear. It is possible that irrigation either reduces climate variability, by reducing the impact of drought events, or increases variability, if the supply of water is itself highly variable.

Integrating the new model with observed sea surface temperatures for the period of 1978–95, Osborne et al. (2007) found that the model reproduced the mean level of yield in India as well as relationships between summer rainfall and yield that are consistent with observed relationships, thus demonstrating that the model is suitable for the analysis of coupled crop–climate interactions. This study comprises two climate simulations—one with interactive crops (GROW; i.e., crop leaf area, root depth, and canopy height respond to changes in the environment), and one with the interannual variability in crop growth removed (FIXED; i.e., a prescribed annual cycle of crop leaf area, root depth, and canopy

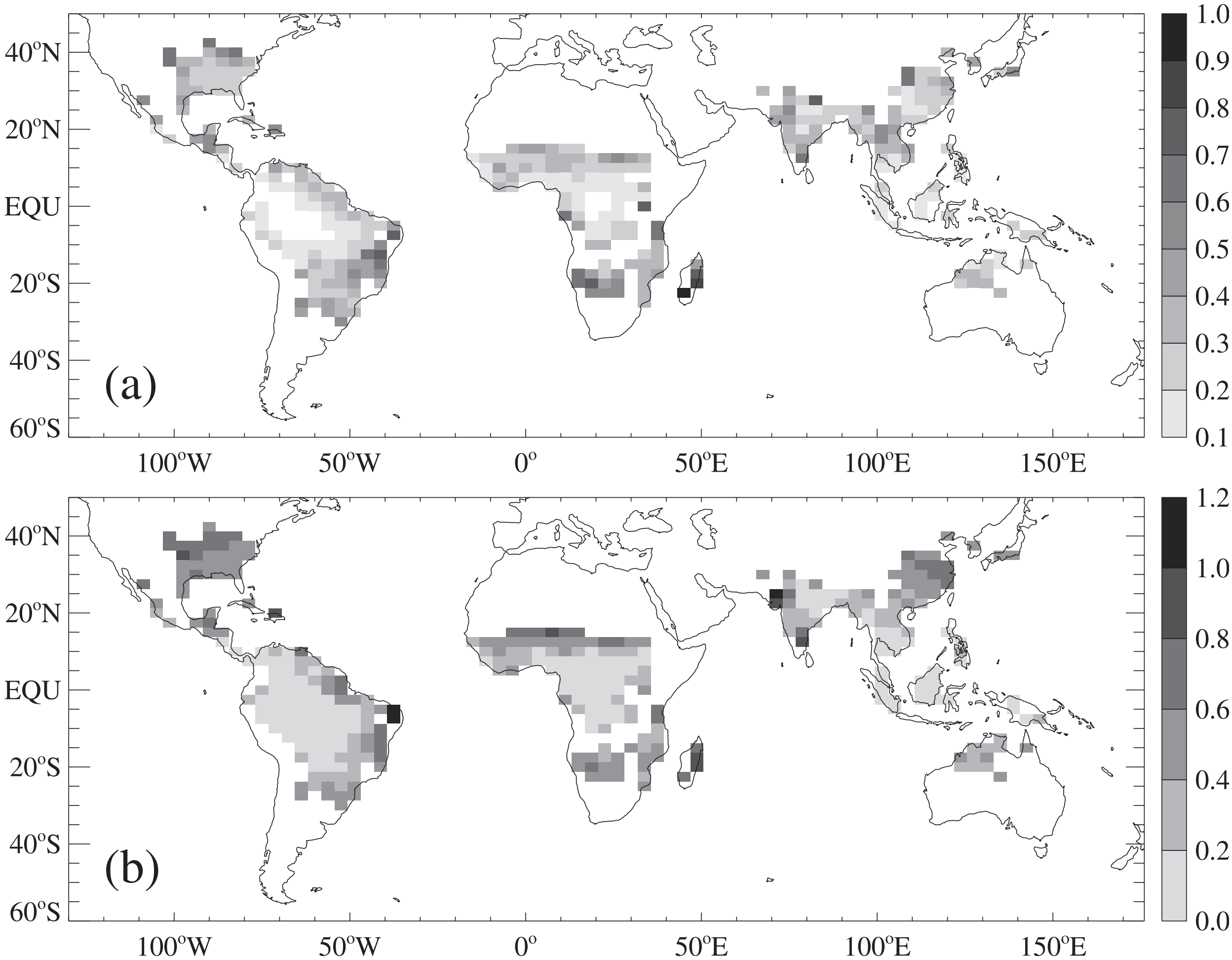

FIG. 3. Std dev of (a) crop yield (ton ha^{-1}) and (b) annual maximum leaf area index (m^2 m^{-2}) from the GROW simulation.

height based on the average performance of the crop from GROW).

3. Evaluation of GROW: Influence of climate on crops

The crop–climate model was integrated with observed sea surface temperature and sea ice fraction from 1957 to 2001, thereby providing a realization of present-day climate and crop growth. In this simulation (GROW) the crop model and atmosphere model are fully coupled, that is, the simulated weather influences when and how the crop grows, while at the same time the simulated crop growth alters the land surface properties, which may in turn influence the surface fluxes and atmosphere.

The crop was only grown at appropriate grid points for the simulation of a tropical rain-fed crop. The selection criteria are based on seasonal distributions of temperature and precipitation. Within these grid points the coverage of the crop PFT was increased at the expense of the C3 and C4 grass PFTs. Because the crop formulation usurped the shrub tile the fractional coverage of shrubs everywhere had to be replaced by the C3 grass PFT to maintain the same total vegetation fractional coverage at each grid point. The resulting fractional coverage of the crop PFT (f_{crop}) is shown in Fig. 1. The distribution of crops can be regarded as the potential growing area of a tropical crop and is used to allow for the examination of crop–climate feedbacks over as large an area as possible. The spatial extent of f_{crop} compares well with observations of the global cropland extent in the tropics (Ramankutty and Foley 1998), with the lowest coverage in the rain forest basins, greater coverage in the Sahel, southeast Brazil, and the central United States, and the greatest coverage in India and China. Replacing C3 grass PFT coverage and not the tree PFTs ensures that the mean climate is not perturbed too much, because the

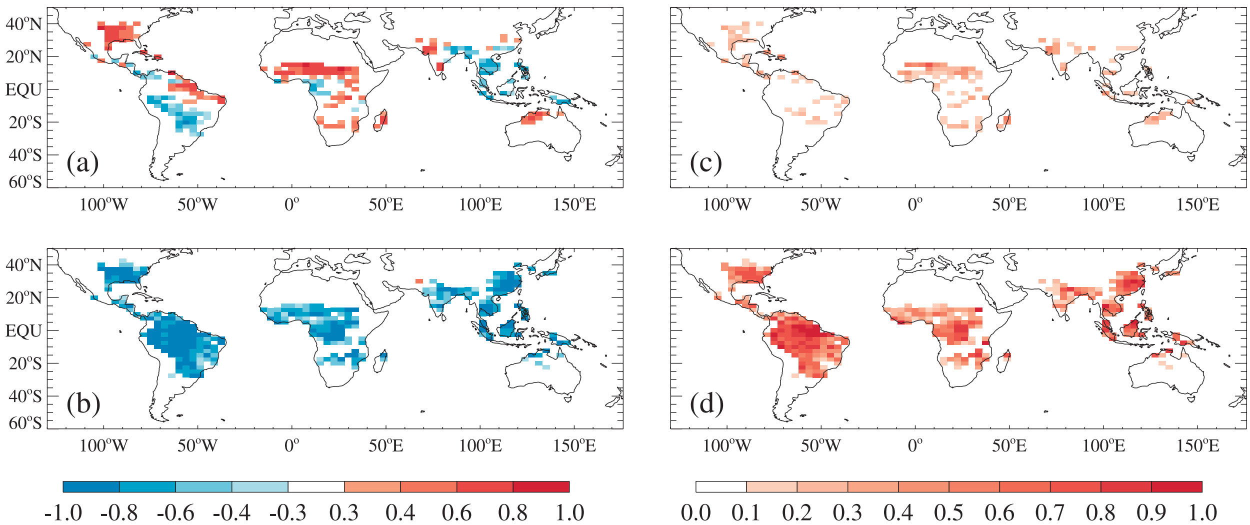

FIG. 4. Linear correlation coefficient between simulated crop yield and (a) growing season precipitation and (b) temperature; and (c), (d) the fraction of yield variance explained by each, respectively.

tropical forests have an appreciable influence on global climate (Osborne et al. 2004).

Examples of the seasonality of crop growth in the model are shown in Fig. 2. In the humid tropics the lack of a dry season allows multiple crops to be grown each year, which appears as an almost constant LAI in the multiyear mean. Stronger seasonality is evident for other regions where growth is limited to specific parts of the year by water availability or low temperatures. For example the peak in LAI for the southeast United States is during summer while in India the peak is later, after the peak in monsoon rainfall. For semiarid regions such as the Sahel and parts of India, the seasonal variations in vegetation coverage are similar to that of natural vegetation, which is also dependent on seasonal rainfall for growth (Lawrence and Slingo 2004a). However, at the end of the growing season, crop vegetation cover is dramatically reduced when the crop is harvested, while natural vegetation senesces over a longer time period during the dry season.

The interannual variation of crop yield and seasonal maximum LAI is shown in Fig. 3. The two patterns of variability are broadly similar because of the positive association between leaf area and biomass accumulation. The lowest variability occurs in the humid tropics where temperature and soil moisture are nonlimiting. Further from the equator, greater variations in crop size and yield occur with some spatial variability at the regional scale. For example, within India greater variability is seen for the southern and northwestern regions compared to central and eastern parts. Challinor et al. (2003) show that observed yields are most variable in the northwest of India, with lower variability in the south.

To understand the causes of variability in crop productivity, contemporaneous correlations between end-of-season yield and growing season precipitation and temperature were determined (Fig. 4). It is important to note here that correlations have commonly been used to infer an influence of climate on crop productivity despite the possibility that the crop may have an influence on the climate. The simulated relationship between yield and precipitation is generally positive, with the highest correlations in regions where mean rainfall is relatively low and variable. Correlations between observed climate and crop yield variations have been derived by several authors for a selection of crops at different spatial scales. At the global scale, Lobell and Field (2007) found a positive relationship between precipitation and yield of barley, rice, and soya bean (a crop with growing area and morphology similar to groundnut).

The simulated relationship with temperature is strong and negative, implying that the thermal time control on crop duration is important for determining biomass accumulation and yield. Lobell and Field (2007) found negative relationships between observed yield and temperature for six out of the seven crops they examined. The regions of negative correlations between yield and precipitation in Fig. 4a are due to a strong local positive relationship between temperature and rainfall in the model. Figures 4c–d compare the relative contributions of each variable to yield variability. Clearly, temperature is the dominant variable for much of the tropics, except for the driest regions of the Sahel and northwest India.

This comparison with observations is not to validate the model in order to subsequently use it for yield

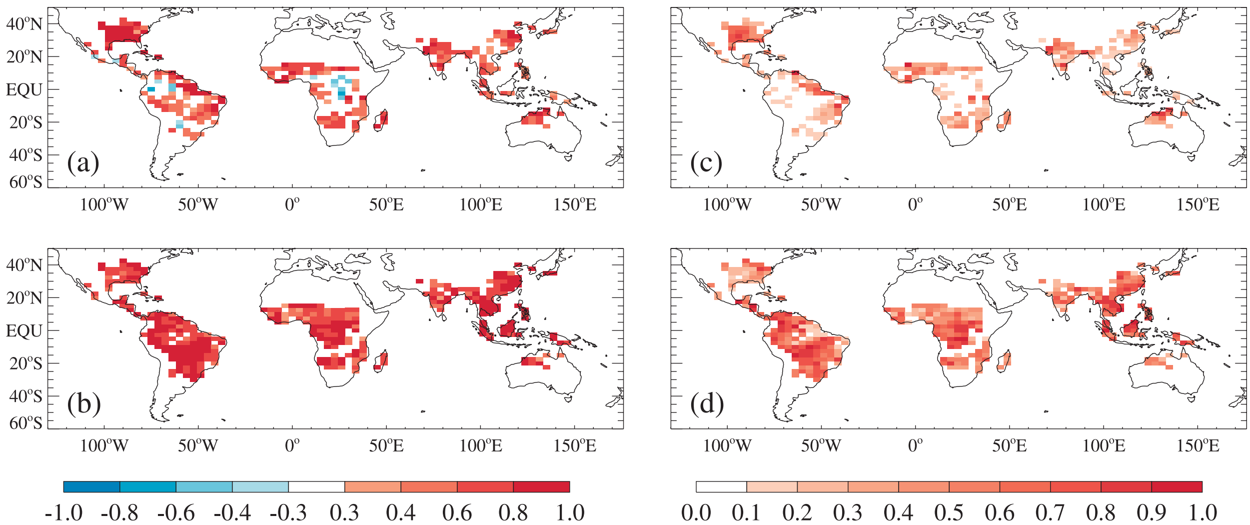

FIG. 5. Linear correlation coefficient between simulated crop yield and (a) crop transpiration rate and (b) growing season duration; and (c), (d) the fraction of yield variance explained by each, respectively.

prediction, but to demonstrate that the direction of the modeled response of the crop to climate fluctuations is in agreement with that observed. At the regional scale, positive relationships between precipitation and yield are simulated in major groundnut growing regions: India, the Sahel, and the southern United States. Challinor et al. (2003) found that groundnut yield variations in northwest and eastern parts of India were positively related to rainfall fluctuations. At the country scale Krishna Kumar et al. (2004) determined the relationship between the yield of several crops and June–September rainfall and found significant positive relationships for rice, wheat, and pulses as well as groundnut.

In Africa, Stige et al. (2006) examined the relationship between crop yield in several regions with climate indices such as ENSO, which has associated teleconnections with rainfall and temperature in parts of Africa. Strong associations were found for maize, sorghum, millet, and groundnut, which were strongest in the Sahel, and equatorial and southern Africa. To extend the evaluation countries within the Sahel, groundnut yield data from the Food and Agriculture Organization of the United Nations (FAO 2006) were correlated with the collocated rainfall from the global dataset of the Climate Research Unit, University of East Anglia (Hulme 1992). Both the yield and rainfall data were detrended using the first difference method. Significant ($p < 0.1$) correlations were found between variations in June–September rainfall and groundnut yield in Senegal ($r = 0.60$), Mali (0.61), Nigeria (0.27), and Sudan (0.28). For the southeast United States, state-level groundnut yield data from the U.S. Department of Agriculture National Agricultural Statistics Service (online at http://www.nass.usda.gov) were correlated with rainfall. Yield was positively correlated with June–September rainfall in Alabama ($r = 0.51$) and Georgia ($r = 0.66$).

To examine the importance of key crop growth properties for determining yield, the correlation analysis was repeated with crop water use per day (which is proportional to daily biomass accumulation) and crop duration (which determines the period of biomass accumulation). Figure 5 shows that for most grid points crop duration explains the greater proportion of yield variance, consistent with the relationship with temperature in Fig. 4. The rate of crop development from one growth stage to another is determined by thermal time, (the product of time and temperature above a crop-specific threshold). Therefore, in warmer environments the crop develops faster and consequently has less time for biomass accumulation than the same crop experiencing cooler temperatures.

Transpiration is closely linked to biomass accumulation and represents a measure of how well the crop is growing per day. Its rate is strongly dependent on the leaf area index and stomatal conductance, which in turn is sensitive to soil moisture availability and atmospheric humidity deficit. Figure 5a shows that transpiration variability is important for crop yield in most regions, except the humid tropics, while Fig. 5b shows that yield and growing season duration are strongly related throughout the growing area. Growing season duration generally explains the greater portion of crop variance, especially in the humid tropics, while transpiration variability is of greater importance in parts of the southern United States, the Sahel, India, and the

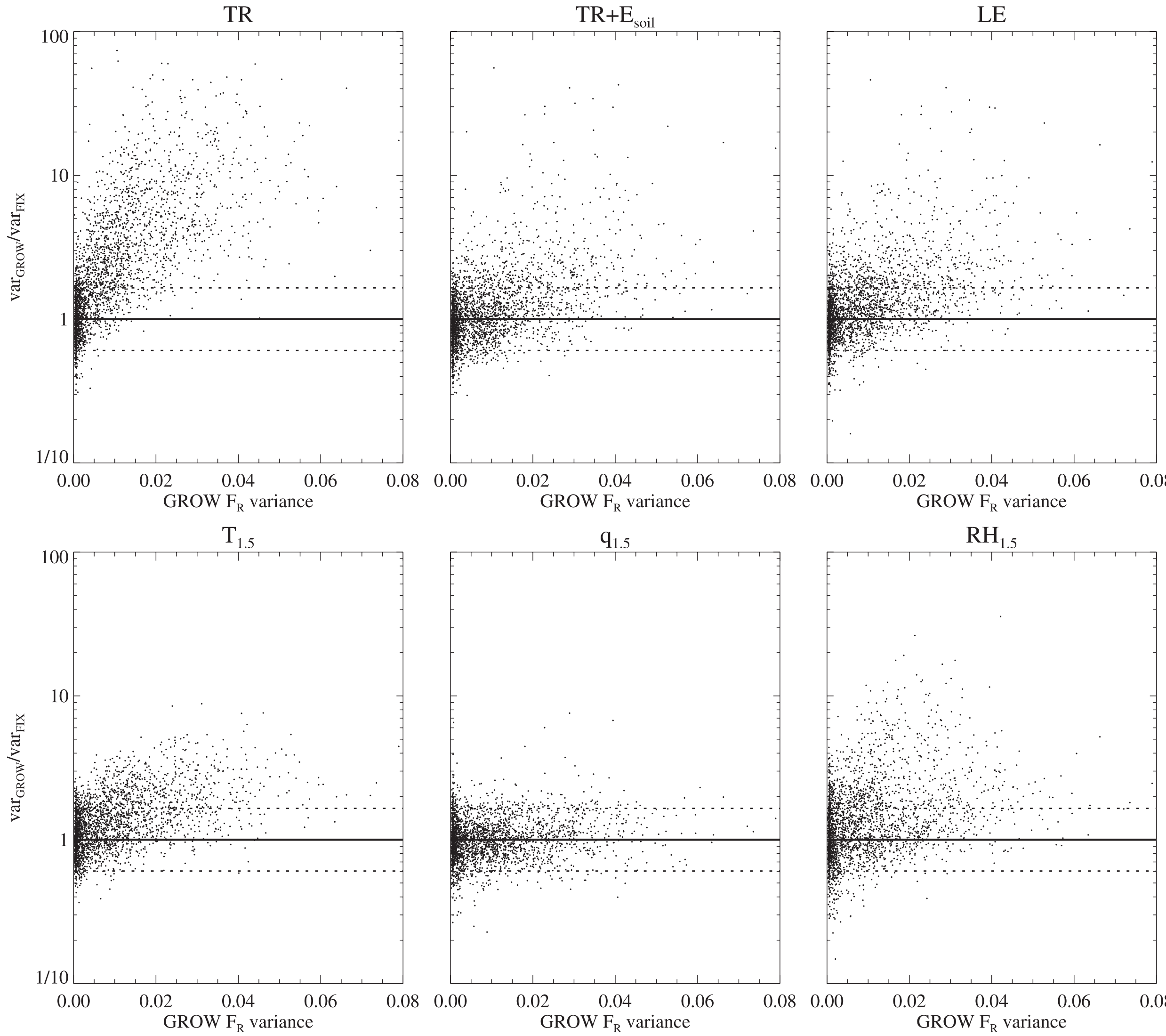

FIG. 6. Change in (top) variability of monthly mean transpiration, the sum of transpiration and soil evaporation, and latent heat flux, and (bottom) temperature, specific humidity, and RH at 1.5 m against radiative fraction (F_R) variability in GROW. Data plotted for crop grid points only when monthly LAI in FIX is greater than 30% of annual maximum, that is, during the median crop growing season. Dashed lines indicate change in variance significant at the 5% significance level ($p < 0.05$ and $p > 0.95$).

eastern coast of Brazil (i.e., regions characterized by periods of water stress).

The crop simulation in the coupled model is in accordance with basic crop science responses, while being a consistent part of the land surface. In the next section we examine whether the associated variations in crop characteristics influence the climate that the crops experience.

4. Influence of interactive crops on their environment

To isolate the impact of the interactive crop on climate a parallel climate simulation for the same time period was performed with the interannual variability in crop growth removed (FIX). This section describes the setup of the FIX simulation, then compares the mean climates of FIX and GROW, before examining any changes to climate variability. Finally, the role of crop growth in the context of regional land–atmosphere interactions is investigated. Both FIX and GROW have prescribed interannually varying sea surface temperatures and therefore each is a single realization of climate for the period of 1956–2001. Differences between simulations may occur simply because of the nondeterministic nature of the climate system. However, the systematic response of the simulated changes to variability with crop variability

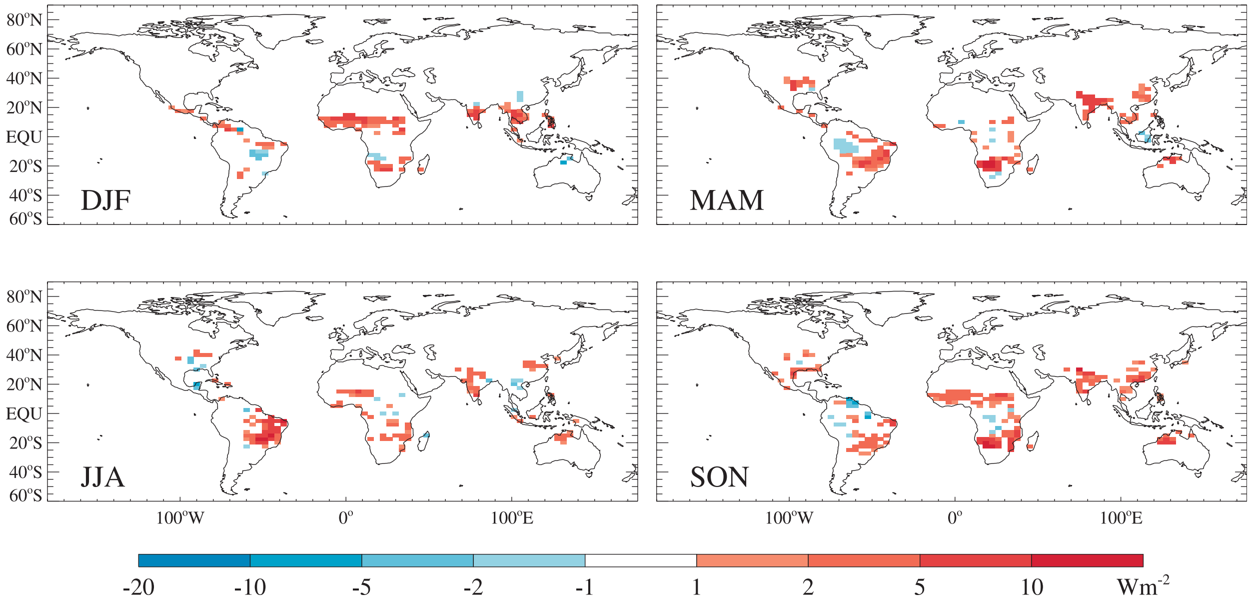

FIG. 7. Difference in std dev of latent heat flux. Changes shown over crop grid points only, where significant at the 10% level and where mean is greater than 10 W m^{-2}.

provides confidence that the results are not solely due to internal variability of the climate model.

a. *Experimental design*

To remove crop variability in the FIX simulation an average crop-growing season was prescribed for each grid point based on the results from GROW. Figure 2 shows the simulation of crop LAI in a range of environments in GROW. Because the sowing date of the crop is primarily a function of soil moisture, the timing of the crop-growing season is strongly determined by the seasonality of simulated rainfall. This is clearly seen in the semiarid regions of India and the Sahel. In humid regions (e.g., the southeast United States) the crop-growing season begins as soon as the temperature is high enough for crop emergence to occur based on its

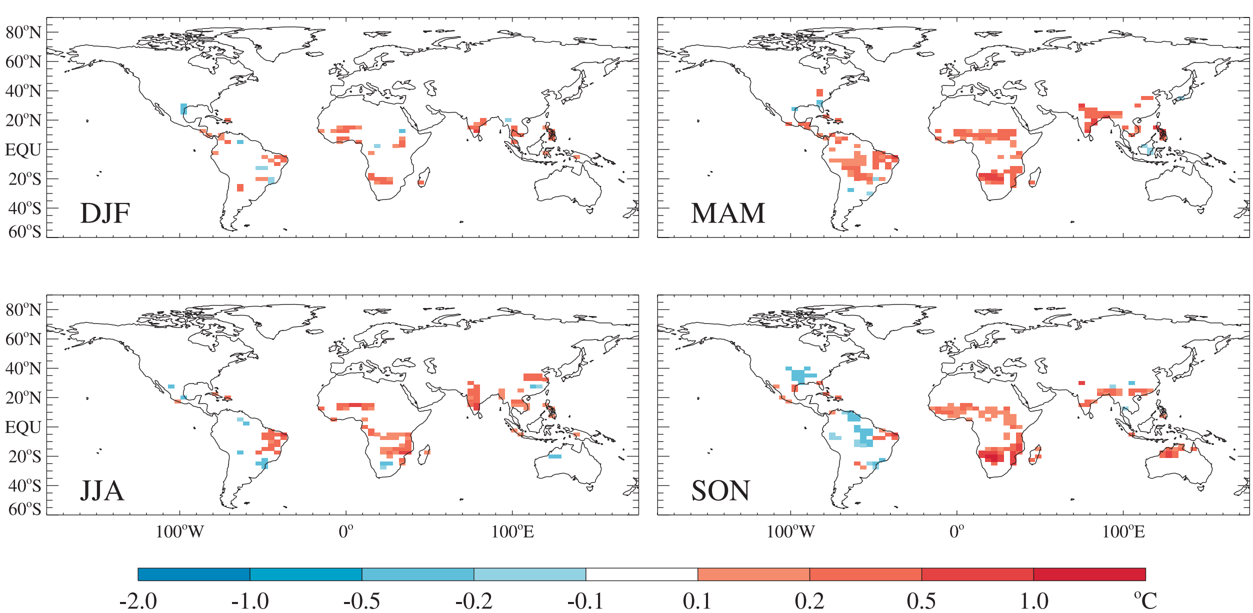

FIG. 8. Difference in std dev of 1.5-m temperature. Changes shown over crop grid points only and where significant at the 10% level.

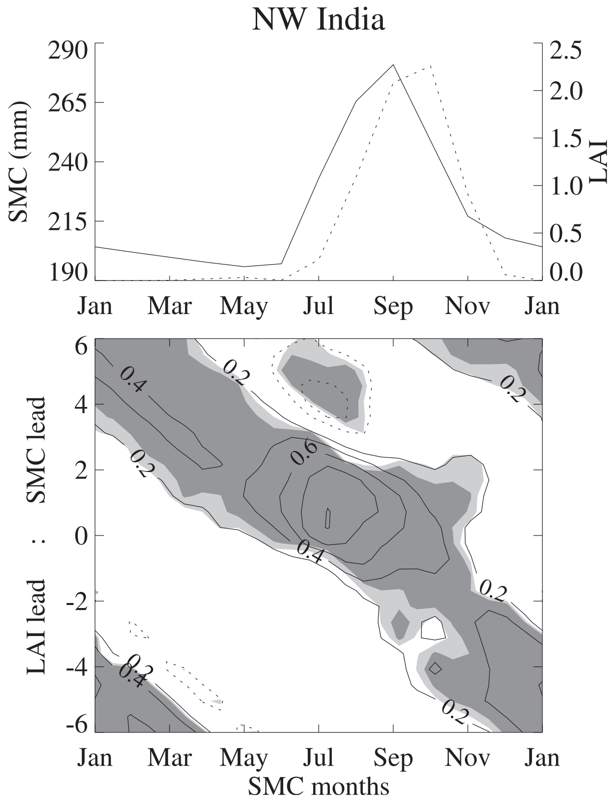

FIG. 9. (top) Climatologies of SMC (solid line) and LAI (dashed line) in northwest India. (bottom) Lag correlation between SMC and LAI. Gray shading indicates correlations significant at the 5% (light) and 1% (dark) level ($df = 41$).

thermal time requirements. As already noted, if sufficient soil moisture is available at the end of the primary growing season, a second crop can be sown in the model.

The interannual variability in crop growth is represented by the gray shading. The greatest variability is simulated in southeast India and is due to variations in the timing of monsoon onset as well as subsequent rainfall amounts that affect the soil moisture content and rate of canopy expansion. For the other regions, variability in the onset date is the strongest determinant of LAI variability in any given month during the growing season, demonstrating that the interactive sowing date algorithm is a crucial component of GLAM–MOSES and emphasizing the need for sowing date observations to validate this model response. A large range of LAI is also simulated for the second growing season in the southeast United States. In some years low soil moisture at the end of the main growing season means that a second crop is not sown or, if it is, does not grow as well as the main crop. In southeast India, a second crop is rare while in the Sahel it is consistently sown but does not grow as well as the previous crop because of diminishing soil moisture content.

As shown in Fig. 2, the multiyear mean LAI can lie outside of the interquartile range of LAI during periods of low LAI (i.e., sowing and harvest) when the non-negative nature of LAI skews the distribution. However, the annual cycle of the median LAI has a more realistic annual cycle and was therefore used to represent the seasonal evolution of crop LAI each year in FIX. Annual cycles of canopy height and root depth were derived from the median LAI using allometric relationships. The land surface characteristics important for land–atmosphere interaction, such as albedo and roughness length, were then derived within MOSES from LAI and canopy height. For details of these formulations see Lawrence and Slingo (2004a).

b. *Mean climate*

GROW and FIX have slightly different mean vegetation states resulting from the use of the median LAI in FIX. Before analyzing any changes in the variability of climate between GROW and FIX the mean climates were compared. The largest changes to mean climate were observed over the humid tropics where the specification of LAI in FIX is not representative of a crop-growing season (see bottom panels Fig. 2). In semiarid regions, the difference between mean climates was small.

No major changes in seasonal mean precipitation exist, but slight changes to near-surface temperature and specific humidity develop, particularly in the Amazon and Congo basins; GROW is cooler and drier than FIX because of the interactions of changes to low-level wind and surface fluxes. Surface evaporation is lower, while sensible heat flux is greater because of stronger low-level winds. The variation of LAI in GROW above and below the mean have disproportionate affects on the determination of surface fluxes; more specifically, the impact of low LAI is greater than that of higher-than-average LAI.

c. *Interannual variance*

To examine the local relationship between crop variability and surface fluxes, the top panels of Fig. 6 show the change in variance of surface evaporation variables as a function of the corresponding variability in crop size (represented by radiative fraction, F_R) for the same grid point and month. The analysis is restricted to crop grid points only and months where the mean LAI exceeds 30% of the annual maximum (i.e., during the main crop-growing season only and avoiding occasional second growing seasons). Change in variability is shown as the ratio, which is also used as the statistic to test for significance against the F distribution. The F_R was identified

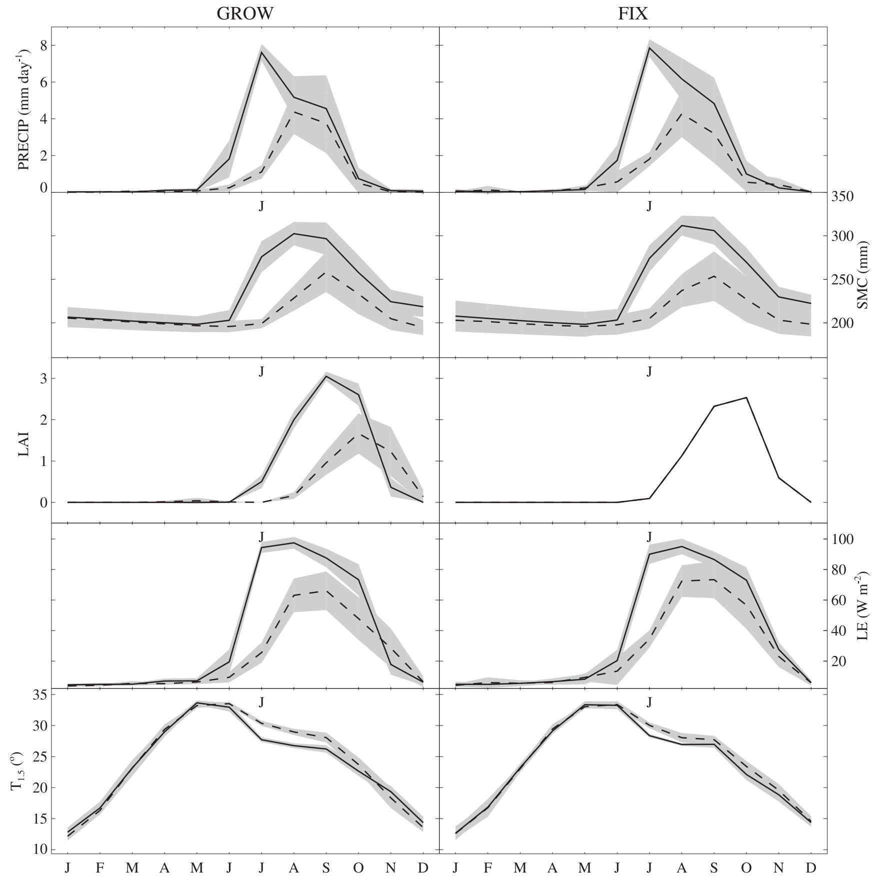

FIG. 10. Composites of years with the 10 highest (solid) and lowest (dashed) July precipitation in northwest India for (left) GROW and (right) FIX. Fields shown are (from top to bottom) monthly mean precipitation, soil moisture content, leaf area index, latent heat flux, and 1.5-m temperature. Gray shading is the confidence interval ($p = 0.1$).

by Crucifix et al. (2005) as a useful parameter when analyzing the impacts of vegetation on surface albedo and evapotranspiration and is a function of the fraction occupied by the crop in the grid box and its leaf area index:

$$F_R = f_{\text{crop}}(1 - \exp^{-\text{LAI}/2}).$$

Grid points with the highest crop coverage and months with the highest crop LAI variability will therefore have the greatest variability in F_R. By experimental design the variance of F_R in FIX is zero because f_{crop} is constant in time and the variability of LAI has been removed.

The largest increases in variability are observed for transpiration (TR) for which very large increases occur during the start of the growing season when mean transpiration rates are low. There is a positive relationship between change in variance and the variability of F_R in GROW, suggesting that the amount of crop variability and the fractional coverage of the crop is important. Changes in leaf area will alter the area of transpiring surface directly, while changes in crop height will impact surface fluxes via changes to the turbulent transfer. When transpiration is combined with evaporation from the soil below the canopy (E_{soil}) the increases in variance are not as large, which implies a compensation between leaf area and the exposure of bare soil, that is, increased LAI leads to greater transpiration but also decreases the area of bare soil exposed to the atmosphere and hence decreased evaporation from the surface soil moisture store. This compensation will be greatest in wet environments when evaporation is not moisture limited.

The response of surface latent heat flux is similar to that of the sum of bare soil evaporation and transpiration, implying that canopy evaporation either does not respond to crop variability or that it is a small component of surface evaporation. The water-holding capacity of vegetated canopies in MOSES is given by the equation $C_m = 0.5 + 0.05\text{LAI}$ (kg m^{-2}). The presence of a canopy capacity when there is no vegetation cover

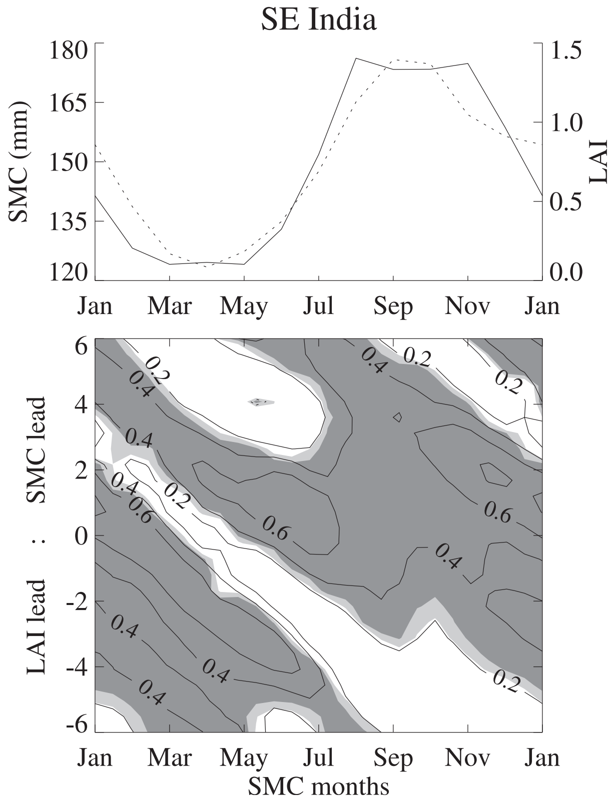

FIG. 11. Same as Fig. 9, but for southeast India.

means that variations in LAI alone do not have a large impact on canopy capacity. This MOSES parameterization for crops appears counterintuitive for crops and therefore requires reexamination for future versions of GLAM–MOSES.

The magnitude of variability in surface albedo introduced by interactive crops in GROW was significant for many regions but small, and did not lead to a significant increase in the interannual variability of net shortwave radiation at the surface.

Figure 7 shows the pattern of changes in variability of seasonal mean latent heat flux. Because the ratio of variance is the test statistic, contour levels have been chosen relating to significance levels. Surface latent heat flux variability is greater in GROW compared to FIX in many tropical regions. The response is seasonal, with the largest changes occurring in the drier months because an occasional crop-growing season dramatically alters the surface fluxes and increases the variability.

Following the change to surface evaporation, changes in the near-surface climate might be expected. The bottom panels of Fig. 6 show the response of near-surface temperature, and specific and relative humidities against crop variability. The systematic response of the change in variability with crop variability is a strong indication that the changes are not due to internal variability of the climate system. Most notable is that while temperature is influenced by crop variability, specific humidity variability does not change, implying that atmospheric advection of moist air may compensate when surface evaporation is low and that the boundary layer is efficient in moving high levels of moisture to the free atmosphere when surface evaporation is high.

The spatial pattern of changes to near-surface temperature variability is shown in Fig. 8. Variability increases in India, the Sahel, southern Africa, and Brazil in GROW compared FIX. The variability of precipitation was not affected by variations in crop LAI at the land surface (not shown). The change in variability of growing season mean temperature was also significantly altered for many regions. The largest changes were simulated over eastern Brazil where the standard deviation of growing season temperature was 1.7°C in GROW and 1.0°C in FIX; therefore, dynamic crops can be viewed as having contributed 40% of the interannual variability in GROW. In India and the Sahel, variability was increased by up to 33% and 39%, respectively.

While the positive relationships in Fig. 6 suggests a physical link between crop variability and surface temperature, it should also be considered that this effect is caused indirectly, via changes to soil moisture variability. To examine this, changes in soil moisture variability were plotted against crop variability and it was found that interactive crops did not systematically alter the variation in soil moisture (data not shown). Therefore, the possibility that the changes to climate variations are due to changes in soil moisture can be discounted.

d. *Regional analysis*

This section examines the role of dynamic crop growth within regional land–atmosphere interactions. The conceptual framework for considering the importance of dynamic crop growth is that following a rainfall event, the soil moisture content increases, which affects surface flux partitioning, boundary layer development, and, potentially, the likelihood of subsequent convection and rainfall events (Taylor et al. 2003). Our hypothesis is that interactive crops, by responding to the anomalous soil moisture, can influence the occurrence and/or strength of this feedback loop. The dynamical growth of crops, in response to rainfall anomalies can potentially (i) alter the surface climate by changing land surface properties, and (ii) add memory to the system because anomalous growth leads to variations in crop size after the initial rainfall anomaly.

The response of the crop to rainfall fluctuations is the first critical path in the feedback loop. Figure 4 shows that the relationship between crop yield and

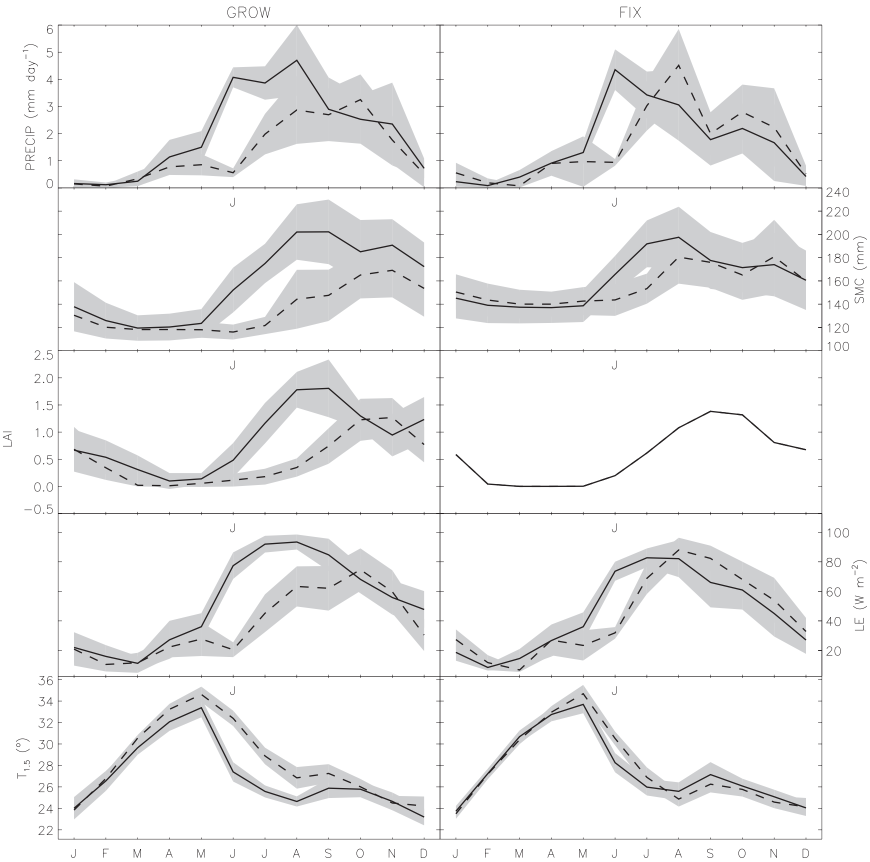

FIG. 12. Composites of years with the 10 highest (solid) and lowest (dashed) June precipitation in southeast India for (left) GROW and (right) FIX. Fields shown are (from top to bottom) monthly mean precipitation, soil moisture content, leaf area index, evaporative fraction, and 1.5-m temperature. Gray shading is the confidence interval ($p = 0.1$).

precipitation is strongest in regions where there is sufficient variation in rainfall amount for soil moisture deficits to occur and crop growth to be water limited. We shall therefore focus on the following three such regions: northwest India, southeast India, and the Sahel. For both the GROW and FIX simulations, composites of 10 yr with the highest and lowest rainfall amounts in particular months critical for crop growth have been constructed and compared to elucidate the importance of dynamical crop growth.

1) NORTHWEST INDIA

Figure 9 illustrates the strong relationship between soil moisture and crop LAI variations in northwest India. It is clear from both the mean annual cycles and correlation coefficient that LAI lags soil moisture variations by 1 month reflecting the effects of variations in growth on subsequent crop size. The negative relationship between soil moisture in July and LAI 4 months later is a consequence of the growing period of the crop; a wet July is associated with an early onset of the monsoon and crop-growing season so the crop is more likely to be harvested (i.e., reduced LAI) by November.

Figure 10 shows the evolution of wet and dry years, compositing on July precipitation (the month with the greatest correlation of soil moisture variations with crop LAI). For both GROW and FIX, a large difference in July precipitation exists between wet and dry years. In wet years precipitation reaches 8 mm day^{-1} in both GROW and FIX, while in dry years it is limited to approximately 1 mm day^{-1} in GROW and 2 mm day^{-1} in FIX. This leads to significant difference between wet and dry years in soil moisture content (SMC), latent heat flux (LE) and near-surface temperature ($T_{1.5}$) in both GROW and FIX. In the months following the initial rainfall anomaly, the statistical difference between wet and dry years in near-surface temperature persists in GROW until September, but only until August in FIX. This can be related to a greater persistence in the latent heat flux in GROW, which will influence temperature through the cooling effect of evaporation. In turn, the separation in latent heat flux can be linked to the crop leaf area index,

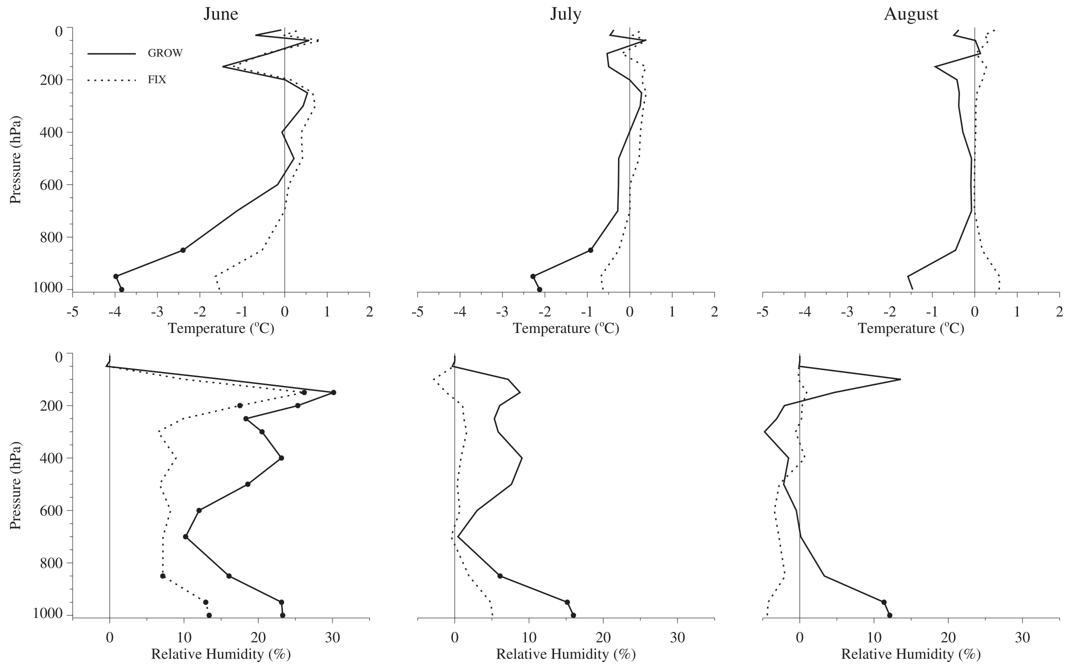

FIG. 13. Vertical profiles of the difference between wet and dry composites based on June rainfall in (top) temperature and (bottom) RH for GROW (solid) and FIX (dashed) simulations. Dots indicate differences significant at the 95% significance level.

because the difference between wet and dry years is largest in August and September, while the separation in soil moisture is no longer significant in September in GROW, but persists until September in FIX.

The changes to the persistence of the difference between wet and dry years arise without significant changes to either dry or wet years when compared between GROW and FIX. In other words, dynamical crops significantly alter the memory of anomalous rainfall in July without significantly altering the evolution of wet or dry years. In reality, crop production in this region is commonly irrigated, but the processes revealed in this study are useful as an example of what occurs in rain-fed systems.

2) Southeast India

Rainfall in southeast India is distributed over more months of the year than in the north, which leads to a longer period of correlation between soil moisture and crop LAI (Fig. 11). There is a primary peak at the start of the rainy season (June/July) and a secondary peak at the end of the year resulting from the simulation of a second growing season when the soil moisture content is sufficient. The apparent correlation between soil moisture from January to July with LAI at negative lags (i.e., LAI leads soil moisture) is due to the strong persistence of soil moisture anomalies at the end of the rainy season, which gives rise to secondary growing seasons.

Figure 12 shows the evolution of wet and dry years compositing on June rainfall, the month with strongest correlation with crop size. Similar to northwest India, anomalous rainfall is associated with anomalous surface fluxes and climate in the month of compositing and those following. The separation is not confined to surface variables. Figure 13 shows that the separation between wet and dry years in temperature are greatest at the surface but wet years are cooler than dry to a greater depth in GROW than FIX. Relative humidity is significantly greater in wet years compared to dry years throughout the depth of the atmosphere in GROW during June and significantly greater in the lower atmosphere in July and August, while the difference in FIX is no longer significant.

In contrast to northwest India, the separation between wet and dry years in precipitation persists into the following month in GROW, which has a strong reinforcing effect on the soil moisture content anomaly. This means it is not possible to attribute the increased memory of the initial anomaly by near-surface temperature in GROW to the differences in crop leaf area index directly, but rather a positive feedback on to precipitation exists in GROW. The rainfall in dry years is significantly lower in GROW than FIX (-0.38 mm day^{-1}) during June, which suggests that a positive feedback occurs in dry years rather than wet. The subsequent evolution of dry years are significantly different between GROW and FIX. In

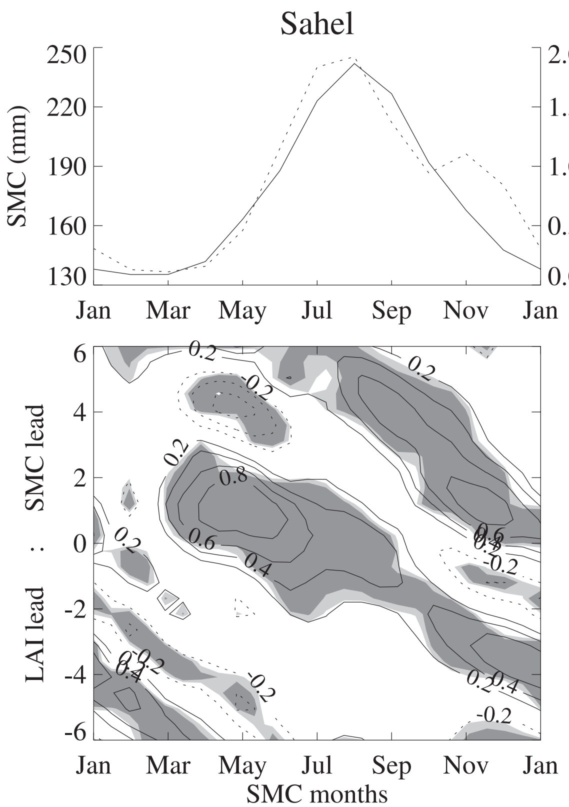

FIG. 14. Same as Fig. 9, but for the Sahel.

June, July, and August, dry years are warmer by 1.88°, 2.00°, and 1.98°C, respectively, associated with lower latent heat flux (-11.4, -23.6, and -24.6 W m^{-2}). The lower rates of evaporation are due to a combination of lower leaf area index (all months) and lower soil moisture content (June and July). Wet years are not significantly different.

3) SAHEL

Crop size in the Sahel is strongly influenced by soil moisture variations at the start of the rainy season (Fig. 14). Similar to northwest India, a negative relationship occurs between soil moisture in May and LAI 4 months later, and similar to southeast India, a secondary peak in correlation occurs after the end of the rainy season associated with the initiation of a second crop-growing season in years when residual soil moisture is sufficient. Composites based upon May rainfall show similar results to that in northwest India with an increase in the memory of the anomaly in near-surface temperature by 1 month (not shown). Figure 15 shows the composites based on rainfall in July. In GROW, a significant difference exists between rainfall in June, July, August, and September, while in FIX the difference only occurs in July, the month of compositing. Therefore, the inclusion of growing crops has introduced a positive feedback on precipitation, which has increased the autocorrelation of rainfall in this particular region. Wet years are not statistically ($p > 0.1$) wetter or dry years drier in GROW than in FIX, but the slight differences combine to create significant separation between the composites in GROW.

At the surface, a separation between wet and dry years is introduced in latent heat flux during July, August, and September in GROW, while the two composites are indistinct in FIX, resulting from the difference in crop LAI and a larger separation in soil moisture. The difference in surface evaporation leads to a larger difference between wet and dry years in near-surface temperature, and introduces a difference in both relative humidity and boundary layer height during August and September. In August, surface latent heat flux is significantly lower during dry years in GROW compared to FIX, implying a reduced local recycling of moisture available for moist convection. For September, dry years in GROW are significantly ($p < 0.1$) warmer by 0.8°C, with boundary layers 16.8 m deeper, reducing the likelihood of the generation of moist convection.

In all three regions, dynamic crop growth increased the response of surface fluxes and climate variables to rainfall anomalies and introduced the memory of the event in surface climate. In northwest India, this could be related to the effect of variations in crop growth rate on crop size in months following the initial rainfall anomaly. In southeast India and the Sahel, positive feedbacks on precipitation were found, which were associated with a reduction of the likelihood of precipitation in dry years rather than an amplification of rainfall in wet years. The impacts were observed for months during the main growing only, therefore, the impact of the simulation of secondary growing season is not considered.

5. Discussion

The results of this study have implications for current frameworks used to assess the possible impacts of future climate on crop production and for seasonal forecasting methodologies. Both currently use climate or weather model output to drive the crop impact model and hence assume that there is no feedback of the crop onto the climate. This study has shown, however, that the dynamic response of the crop may alter the magnitude of climate variations. A natural extension of this work is to examine what impact this feedback may have on the crop simulation itself; that is, to compare the crop simulations of an offline model when driven with the climate of the GROW and FIX simulations. To gauge where the feedback of crop growth on to climate may be

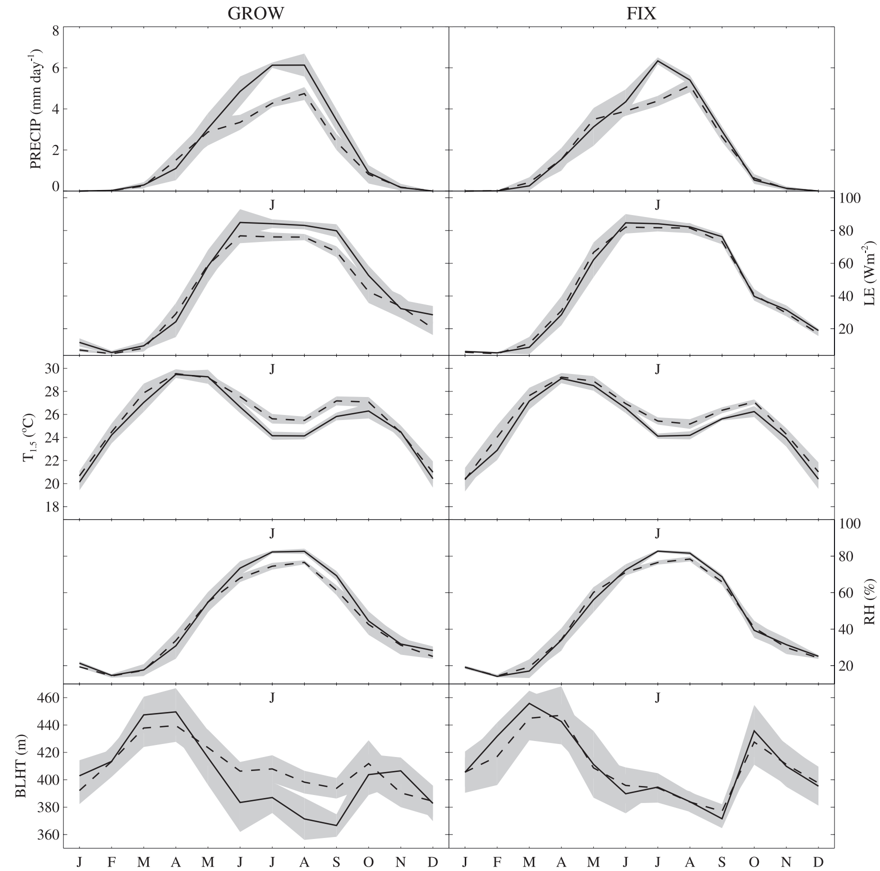

FIG. 15. Composites of years with the 10 highest (solid) and lowest (dashed) July precipitation in the Sahel for (left) GROW and (right) FIX. Fields shown are (from top to bottom) monthly mean precipitation, latent heat flux, 1.5-m temperature, RH, and boundary layer height. Gray shading is the confidence interval ($p = 0.1$).

important for crop yield projections, the simulated change to crop-growing season temperature variability between GROW and FIX at each crop grid point was multiplied by the absolute value of the linear regression coefficient between yield and growing season temperature in GROW at the same grid point. The resulting implied change in yield, expressed as a percentage of the yield variability in GROW, is shown in Fig. 16. Four regions are identified where the coupled nature of crops and climate may be important for crop yield predictions (India, the Sahel, southern Africa, and eastern Brazil), where local climate variability is sensitive to variations in crop growth, and where crop yield is sensitive to variations in surface temperature. Further analysis, with a mechanistic rather than empirical crop model, should therefore focus on these regions. The regional analysis showed that the increase in temperature variability is due to changes at the warm, rather than cold, tails of the distribution associated with low rainfall anomalies, which implies that the projections of yield in drought years might be more sensitive to the inclusion of crop–climate feedbacks than yield in wetter years.

As with any modeling study, the nature of the results are subject to characteristics of the particular model used, and therefore reproducibility of the experiment with other models would be desirable. Other modeling efforts to include growing crops in GCM land surface schemes are active (e.g., Gervois et al. 2004), but as yet are not fully coupled to an atmospheric GCM. In particular, one might expect the results to be dependent on the degree of coupling between the land surface and the atmosphere in the GCM used. In a recent model intercomparison (Koster et al. 2006), the atmospheric model used in this study (HadAM3) was shown to have a weak land–atmosphere coupling strength compared to most other models. Lawrence and Slingo (2005) have shown that this is most likely due to simulation of the atmospheric branch of the soil moisture–precipitation feedback loop. Therefore, the influence of interactive crops on climate may be subject to underlying characteristics of the atmospheric

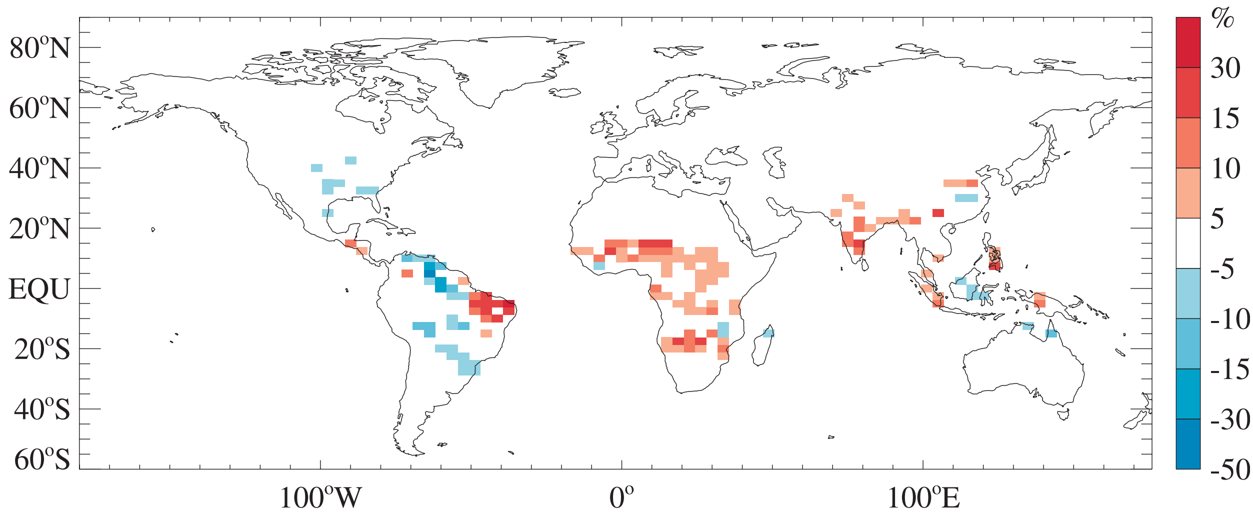

FIG. 16. Inferred impact of change in growing season temperature variability on crop yield variability.

model used. The GLACE metric of coupling strength is not perfectly applicable for this study because it is based upon intraseasonal rather than interannual variability. However, the underlying physical mechanisms are the same at both time scales, so we can hypothesize that the slight impacts on precipitation found in this study may have been greater in an atmospheric model with a different parameterization of the boundary layer and its connection to the free atmosphere.

The results of this study can also be viewed as being indicative of how dynamical vegetation may interact with the climate system at interannual time scales. In a previous study using a dynamic global vegetation model coupled to HadAM3, Crucifix et al. (2005) found that vegetation variability was strongest in semiarid regions where it is driven by precipitation fluctuations, and that these variations increased the variance of surface heat fluxes without impacting precipitation, results consistent with this study. However, that study did not include a realistic parameterization of phenology so that the typical response time scale of vegetation was several years. In this study, crop growth responds to intraseasonal variations in weather, which then projects on to interannual variations in crop size. Nevertheless, the results of this study, in combination with that of Crucifix et al. (2005) and the GLACE study (Guo et al. 2006), suggest that vegetation and soil moisture variations at a range of time scales can influence the variance of surface fluxes, but that the underlying physics of the atmospheric model control the ability of these variations to influence the subsequent generation of precipitation. It is clear that further examination of the physical links between the surface fluxes, boundary layer properties, and free atmosphere in the Hadley Centre model is required.

The caveat of the above statement, however, is that the results described in this study may not differ greatly to the influence of dynamic natural vegetation. In seasonally cold climates, Levis and Bonan (2004) found that prognostic vegetation slowed surface warming in springtime as a result of greater plant transpiration. This study has shown that dynamic crops influence the surface climate in seasonally arid climates. Without the equivalent study to this for comparison, we can only hypothesize that the interactions between growing season onset and climate in seasonally arid regions may well be similar to those identified for crops in this study. However, faster rates of growth in managed cropping systems will result in larger changes in land surface characteristics, which may have a stronger influence on climate. Modeling (Cooley et al. 2005) and observational (McPherson et al. 2004) studies have shown that the seasonal growth of crops, especially the act of harvesting, can alter local climate from that found over natural vegetation. To fully examine this question requires the development of the relevant phenological model for natural vegetation coupled the MOSES land surface scheme.

6. Conclusions

This study was a sensitivity study designed to investigate the importance of dynamic interactive crop growth on the climate the crops experience. Observational evidence has proven that relationships do exist between crops and climate (e.g., Lobell and Field 2007). This paper asked whether a feedback of crops on to the atmosphere exists. In certain regions growing crops do alter the properties of the atmosphere above. More specifically,

- interactive crops modeled as part of the land surface responded to variations in growing season climate in a manner consistent with crop observations; namely, a negative relationship with temperature associated with a reduction in duration, and positive relationship with rainfall associated with water use;
- interannually varying crop land surface properties altered the mean climate of humid tropical regions, compared to the climate simulated with average land surface conditions, while in semiarid regions the mean climate was not altered;
- dynamic crops increased the variability in simulated surface evaporation, which in turn affected the variability of near-surface temperature and relative humidity; for example, growing season temperature variability was increased by up to 40%;
- specific humidity and precipitation were largely unaffected, suggesting that the feedback to large-scale climate was weak, possibly resulting from weak land–atmosphere coupling in HadAM3; and
- interactive crops altered the evolution of local surface climate following anomalous rainfall resulting from the lagged response of crop size to variations in crop growth rate.

Acknowledgments. Tom Osborne would like to acknowledge the ENSEMBLES project, funded by the EC through contract GOCE-CT-2003-505539, and the NERC Centers for Atmospheric Sciences (NCAS). The authors would also like to thank the anonymous reviewers for their efforts and insightful comments on previous versions of the paper.

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